Constraining autoconversion and accretion processes using ARM observations and machine-learning techniques

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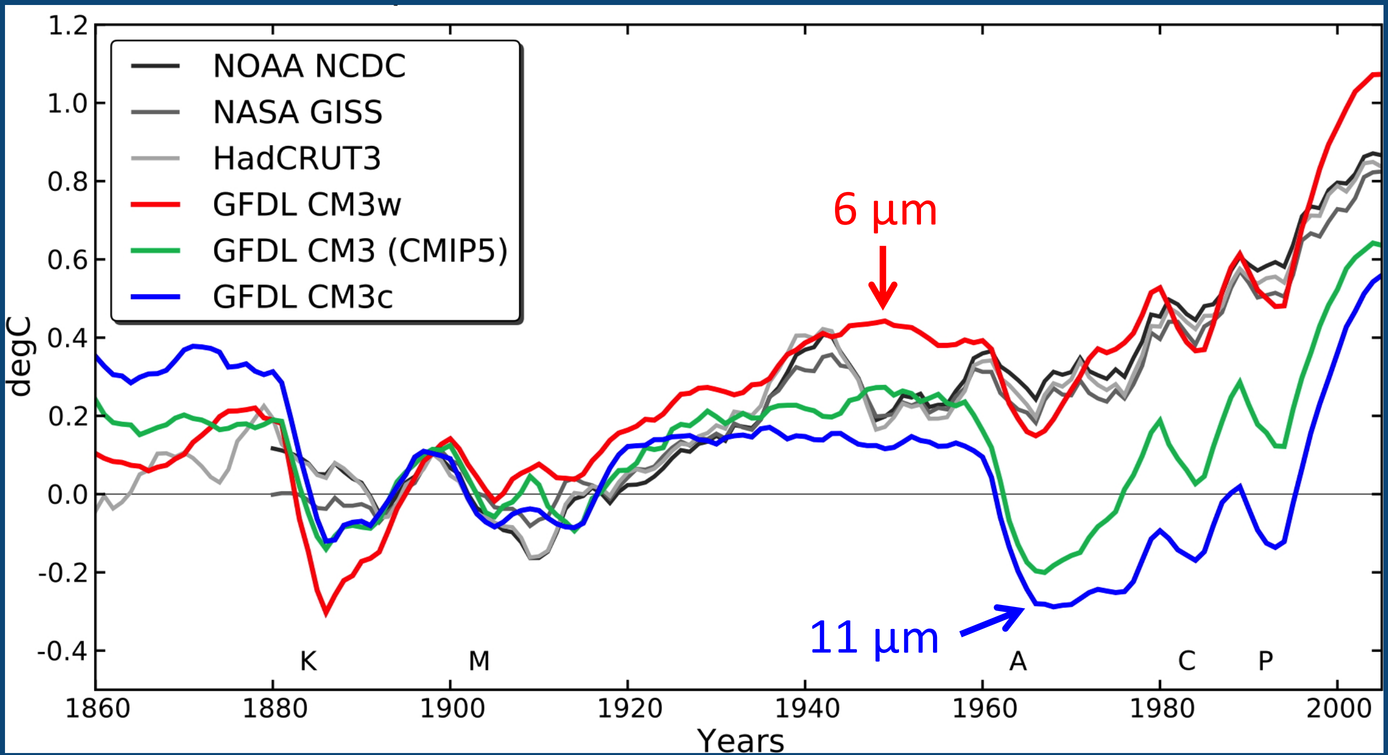
Autoconversion and accretion processes play an important role in warm rain formation

- Warm rain has a great impact on Earth's radiation and water budget

- Related to many outstanding issues in models
  - *the transition from stratocumulus to cumulus*
  - *drizzle too frequent and too light*
  - *Large inter-model spread in precipitation rate in marine boundary layer cloud regimes*

Climate system is highly sensitive to precipitation onset parameter

Temperature anomaly



Golaz et al. (GRL, 2013)

How can we better constrain autoconversion and accretion rates from observations?

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<u>Better understanding</u>

of the relationships between the process rate and cloud/drizzle properties

+

<u>Better cloud and drizzle retrievals</u>

from remote sensing observations

↓

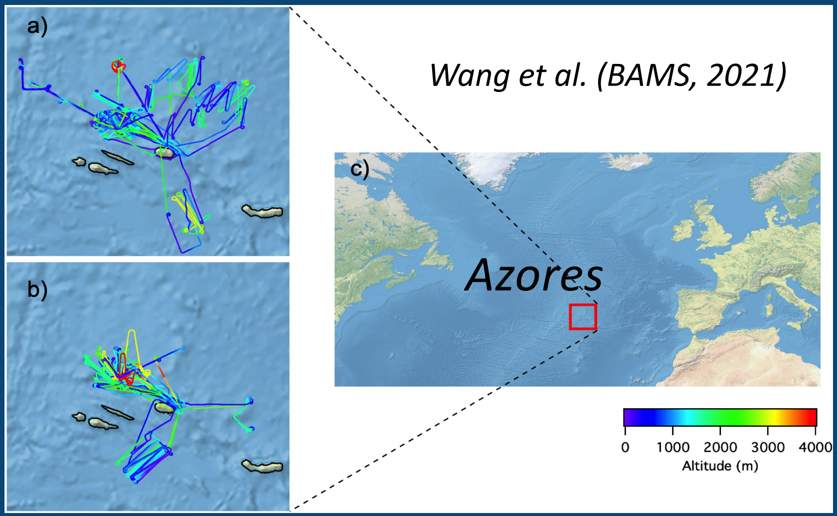
<u>A long term record of autoconversion and accretion rates</u>

for climatology and process studies

(1) Use in-situ cloud drop size distributions (DSD) and machine learning techniques

- Analysed a total of ~93,000 in-situ cloudy DSD (90% drizzling)
- Using the observed DSD as the initial condition, propagating the DSD forward in time for 10 min with the stochastic collection equation
- 10.7M data points for training and 2.5 M for testing

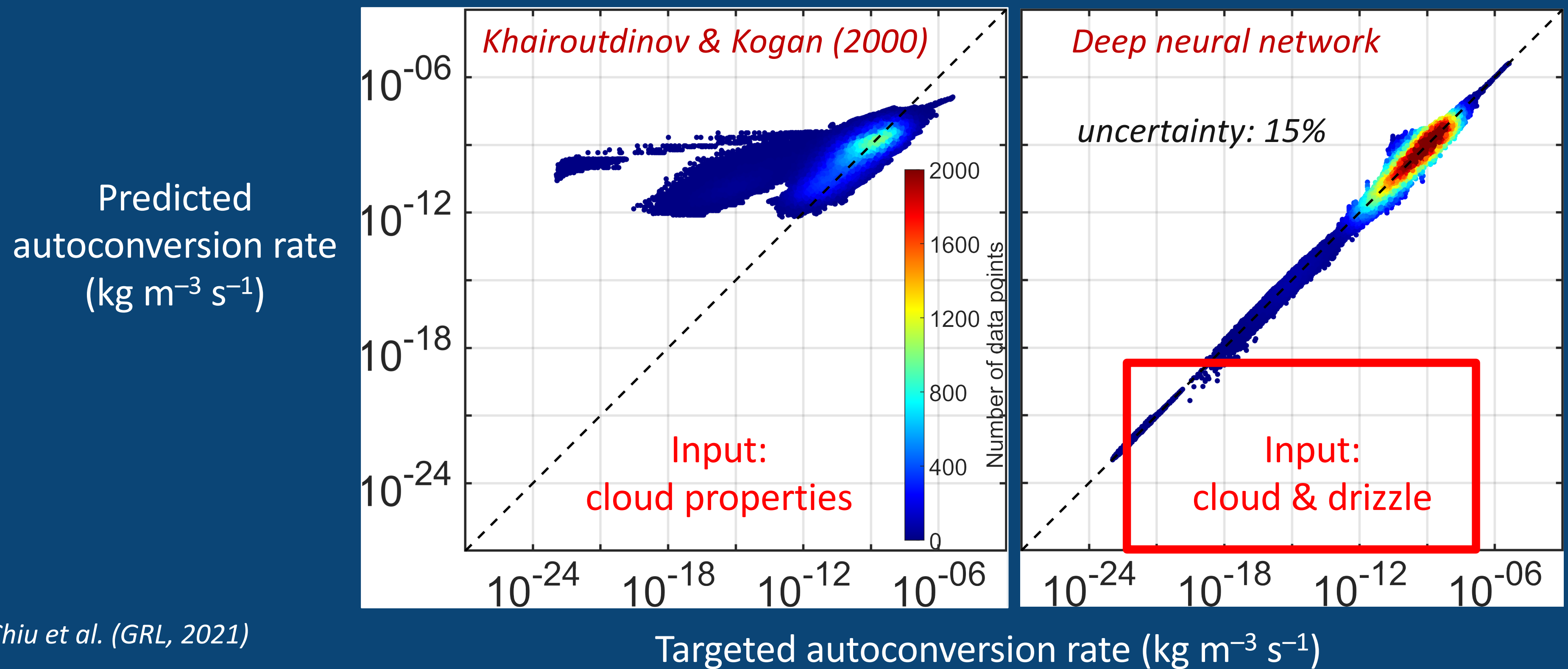
ACE-ENA field campaign (summer 2017 and winter 2018)



Chiu et al. (GRL, 2021; https://doi.org/10.1029/2020GL091236)

Estimate cloud process rate from Artificial Neural Network

- Use deep neural network with 8 hidden layers and 1024 nodes in each layer to train/test the dataset and make predictions



Chiu et al. (GRL, 2021)

Drizzle number concentration is critical for quantifying autoconversion rate

- Drizzle number concentration contains information on the width and evolution of drop size distributions

Our parameterization $P_{au} \propto q_c^{2.02} N_c^{-0.75} N_r^{0.64}$

autoconversion rate | cloud water content | Cloud # of concentration | rain # of concentration

KK parameterization $P_{au} \propto q_c^{2.47} N_c^{-1.79}$

The importance of drizzle number concentration is confirmed by theoretical analyses

- Using the stochastic collection equation and the kernels of Long (1974):

Analytical derivation $$P_{au} \propto q_c^2 \, N_c^{-1} \, N_r + \text{other terms}$$

Our parameterization $$P_{au} \propto q_c^{2.02} N_c^{-0.75} N_r^{0.64}$$

- In the analytical expression, the first term is the one closest to P_{au} for most of the time!

We need to know both cloud and drizzle properties

- Use cloud radar, lidar, and shortwave radiation measurements
- Use an ensemble retrieval framework to find the best estimates of cloud and drizzle number concentration, water content, and drop size

Fielding et al. (2015); Joshil et al. (2020); Wang et al. (BAMS, accepted)

Applying machine learning models to ACE-ENA obs.

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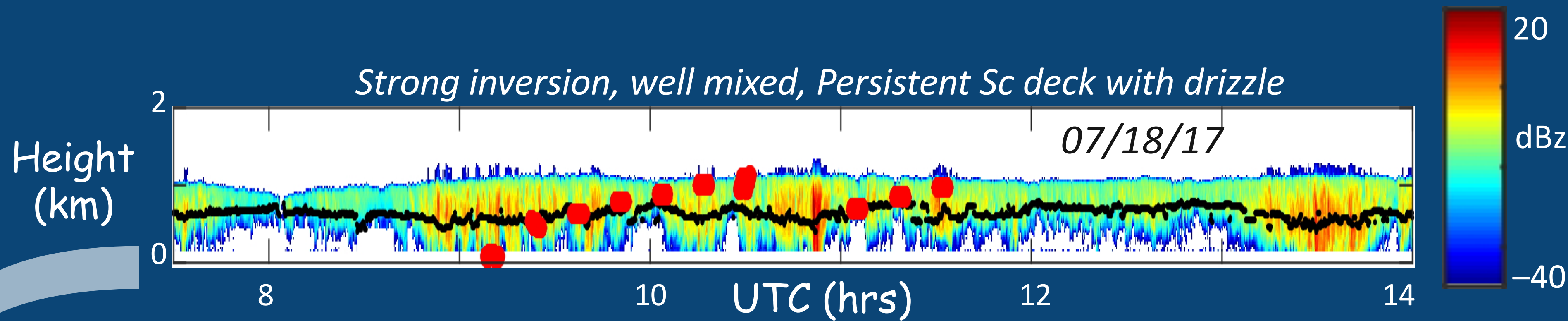
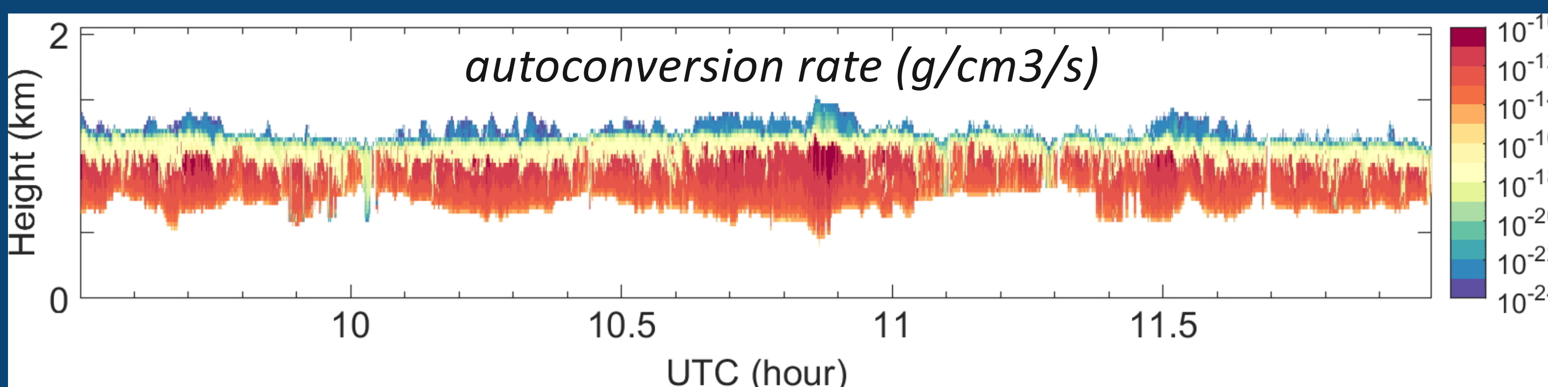


Retrieving cloud and drizzle properties

Machine learning models



Summary

- We have trained machine learning models by in-situ cloud data to predict autoconversion and accretion rates with uncertainty of 15% and 5%, respectively. These models are freely available in the ARM Archive and Github (see *https://doi.org/10.1029/2020GL091236)*

- Our analyses show that drizzle number concentration is critical in quantifying autoconversion rate, which is surprising!

- The new machine learning models have been applied to our ACE-ENA retrievals, producing reasonable autoconversion and accretion rates for further analyses.